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IS THE FORWARD BIAS ECONOMICALLY SMALL?
EVIDENCE FROM INTRA-ERM RATES

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Is the forward bias economically small? Evidence from intra-ERM rates*

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Abstract

For the purpose of testing uncovered interest parity (UIP), rates of European currencies against the DEM offer a distinct advantage: ERM membership or informal ERM association induces statistically significant mean-reversion in weekly rates. Thus, unlike for freely floating rates, there is an expectations signal that has nontrivial variation and is sufficiently traceable for research purposes. When running the standard regression tests of the unbiased-expectations hypothesis at the one-week horizon, we nevertheless obtain essentially zero coefficients for intra-EMS exchange rates (and the familiar negative coefficients for extra-EMS rates). Even more puzzlingly, lagged exchange rate changes remain significant when added to the regression, a feature that seems harder to explain as a missing-variable phenomenon. The deviation from UIP is significant not just statistically but also economically: trading-rule tests reveal that for sufficiently large filters the average profit per trade exceeds transaction costs, and that cumulative gains can be quite impressive. The size of the profits and the patterns from buy versus sell decisions also allow us to reject the risk premium and the Peso hypotheses as separately sufficient explanations.

JEL classification: F31.

Key words: forward bias, transaction costs, trading rule, EMS, ERM

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Introduction

In international finance, one unresolved puzzle is the forward bias: the forward premium systematically mispredicts future exchange rate changes, and does so by far more than conventional risk theories predict.[1] Fama (1984) finds that the variance of the risk premium—or whatever the missing variable is—must be larger than the time-series variance of these conditional expected changes. It is, however, not always obvious how momentous some of these findings are. For example, Fama's moment condition can be met by a missing variable that merely consists of misalignments too small to matter relative to trading costs, combined with expectations that hardly change over time. In the same vein, Froot and Thaler (1990) argue that the expected profits are economically small, especially relative to the residual uncertainty. Bansal and Dahlquist (2000) find that the negative association between forward premium and realized exchange-rate change may be a 70s-80s OECD phemomenenon; in wider and more recent data the picture looks better. De Grauwe (1989) adds that the negative coefficients disappear when the base currency is not the USD. Lastly, the statistical significance of the findings is now being doubted. Roll and Yan (2000) show that the near-unit-root characteristics of the forward premium invalidate the usual standard deviations, and Schotman, Straetmans and De Vries (1997) document a similar phenomenon related to thick tails and outliers in the regressor.

In this paper, we study a new data set, *viz.* 1985-1998 weekly changes in exchange rates against the DEM. We first document a non-trivial short-run predictability of exchange rates created by affiliation to the European Monetary System's Exchange Rate Mechanism (ERM), whether this affiliation be a formal membership like for the Guilder or a market-perceived loose association as for the Swiss Franc. If Uncovered Interest Parity (UIP) holds, the forward premium should pick up this strong predictability. However, our results from standard UIP regression tests on one-week DEM data are not substantially better, and in a sense even worse

[1] The seminal papers are Cumby and Obstfeld (1984) and Fama (1984); Froot and Thaler (1990) offer an excellent (albeit dated) survey; Hollifield and Uppal (1997) bring up a general-equilibrium analysis predicting a small bias; Bansal (1997) shows the bias may be large and asymmetric.

than in other data sets. First, in our Cumby-Obstfeld-Fama (henceforth COF) regression tests of UIP the slopes for European monies are still far from unity, and very sensitive to data period and estimation technique. Second, the autocorrelations are not affected by the introduction of the forward premium as a regressor—evidence that is hard to explain as a missing-variables problem positively contradicts UIP and is Even more interesting is the economic significance of these combined phenomena (predictable rates, and out-of-synch forward premia): a trading-rule test reveals that the cumulative 11-year returns from exploiting the deviations from UIP, over and above the average risk premium, turn out to be a few hundred percentages, in one case even reaching 600 percent. The total size and the details of the returns then allow us to conclude that none of the usual suspects is likely to be singly and fully responsible for such a result. Rather, we need at least a combination, possibly reinforced by a more subtle pricing effect (like the option features stressed by Baldwin, 1990), or a market inefficiency. In short, we think the puzzle has deepened: the amount of money left on the table was quite easy to spot and bewilderingly large. Relative to other work on forex technical trading,[2] our focus is more on UIP and on theories why UIP fails. Other differences are our use of rates against the DEM rather than the USD and, of course, a rule based on reversal rather than momentum.

The structure of the paper is as follows. Section 1 describes the data and shows that European exchange rates, even against the USD, exhibit cross-correlation. This implies substantial short-run predictability for both ERM and semi-ERM currencies. Section 2 demonstrates, via the standard tests of UIP, that one-week forward premiums totally ignore this predictability. To assess the economic significance we provide, in Section 3, results from a trading rule that exploits the predictability. Section 4 discusses the likely or less likely explanations of our findings, and concludes.

1 Predictability in Intra-European Exchange Rates

The data we start from are daily and weekly London exchange rates against the GBP and one-week spot interest rates, both from Datastream (midpoint Barclays quotes, or for USD/BEF, National Westminster quotes). Our data cover almost thirteen years, starting in 1985/6/1 (the date where Datastream's coverage is expanded) to 1998/4/1 (the date Euroland rates

[2]For results from daily data see Levich and Thomas (1993), Neely, Weller and Dittmar (1997), Sweeney (1986), Taylor(1994), and Surajaras and Seeney (1992). For weekly data see Kho (1996). Okunev and White (2003) use monthly data. Intraday data do not seem to work, see Neely and Weller (2001) and Raj (2000).

became quasi-fixed). In our tests, these GBP rates were re-expressed into units of DEM. The ten resulting exchange rates against the DEM are mostly European: four hardcore ERM currencies (BEF, DKK, FRF, NLG) and three intermittently or informally associated with the ERM (CHF, ITL, and as the weakest affiliate, GBP)[3]. To verify whether the findings are indeed typical for European exchange rates we also include three major outside currencies (USD, JPY, CAD).

Exchange rate changes against the USD are commonly accepted to exhibit a slight but statistically clear positive autocorrelation, leading to the profitable momentum-based trading results cited in the introduction. For ERM-member rates, tied to each other by a narrow band, one naturally expects also cross-correlations: currencies that for some reason did not follow the pack immediately must catch up later. In exploratory research that led to this paper we studied daily data against the USD, and found large cross-correlations among ERM-member rates, and weaker cross-links with quasi-members. These links are significant for one- and two-day lags, but rarely beyond that. Also, we found that, from the USD point of view, the DEM was the bellwether currency, with the other European currencies following the DEM's movements against the USD, partly with a lag. Switching data to a DEM basis, we accordingly expect reversal rather than continuation patterns. We indeed found clear negative autocorrelations at lags 1 and 2 for ERM-member rates, and traces of negative autocorrelation for the other European currencies. These results are available on request.

Tests of whether that predictability is reflected in interest-rate differentials are hampered by the fact that for most currencies Datastream offers no long histories of one-day spot rates;[4] but coverage *re* spot one-week rates is adequate. Thus, in Table 1 we document also the autocorrelation pattern for one-week exchange-rate movements rather than overnight ones, first estimated in the regular simple way ("OLS"), and then taking into account the substantial fluctuations in uncertainty ("GARCH", using a GARCH(1,1) variance model and an AR(1) mean equation). We observe strong autocorrelations at lag one for the first four currencies, the ERM core members, many times larger than their standard deviations, and basically no autocorrelation for the other currencies. We also look at subperiods: the period before

[3]Although the Swiss central bank denies intervention, the CHF is widely seen as informally linked to the DEM and, now, the Euro. The ITL was an ERM member but with an unusually wide band. The GBP unilaterally tracked the ECU in 1990-1991 as a prelude to formal ERM membership, in the spring of 1992, but dropped out in September 1992.

[4]Overnight and/or tomorrow/next rates are sometimes available, but in daily tests we'd need one-day spot (that is, second/third working day) because spot forex is delivered on the second working day.

Table 1: First-order autocorrelations, weekly

$$E_{t-1}(\tilde{s}_t) = \kappa_0 + \rho_1 \tilde{s}_{t-1}$$

	Autocorrelation coefficients ρ_1 for individual currencies										averages	
	BEF	DKK	FRF	NLG	CHF	ITL	GBP	JPY	CAD	USD	ERM	$\overline{\text{ERM}}$
	Total period (1985/6 - 1998/3), $\sigma(\rho) = 0.039$											
OLS	*-0.28	*-0.15	-*0.17	*-0.48	-0.03	0.11	0.01	-0.01	0.01	0.02	-0.22	0.03
GARCH	*-0.38	*-0.22	*-0.11	*-0.44	-0.00	-0.01	0.01	-0.01	0.04	0.01	-0.23	0.01
	Early ERM(tight band, 1985/6 - 1992/8), $\sigma(\rho) = 0.052$											
OLS	*-0.36	*-0.30	*-0.13	*-0.51	-0.03	0.03	0.00	-0.03	0.03	0.01	-0.26	-0.01
GARCH	*-0.39	*-0.28	*-0.17	*-0.52	0.02	0.12	-0.01	-0.04	0.00	-0.01	-0.27	0.01
	Sept 92 - end 93 (turbulence, 1992/9-1993/12), $\sigma(\rho) = 0.12$											
OLS	0.02	0.01	*-0.24	*-0.45	0.02	0.13	0.04	0.02	-0.08	0.08	-0.13	0.04
GARCH	-0.21	0.01	*-0.26	*-0.32	-0.00	0.13	0.07	0.08	-0.21	0.04	-0.16	-0.02
	Late ERM(wide band, 1994/1 - 1998/3), $\sigma(\rho) = 0.066$											
OLS	*-0.39	-0.09	*-0.17	*-0.26	-0.08	0.11	-0.03	-0.13	0.09	-0.01	-0.20	0.01
GARCH	*-0.42	*-0.18	*-0.16	*-0.26	-0.05	-0.08	-0.03	-0.13	0.11	-0.01	-0.21	-0.03

Key to Table 1. The variables s_t are weekly percentage changes in the exchange rate against the DEM. Autocorrelations are estimated using OLS and GARCH. The averages shown are for the first and second sets of five currencies, respectively, labeled somewhat inaccurately "ERM" and "$\overline{\text{ERM}}$". An asterisk denotes significance at the 1 percent level (one-sided)

September 1992 with a narrow ERM band and many formal re-alignments, the turbulent Sept92-Dec93 period, and the more quiet wide-band period as of 1994 that ended in the fixed rates for Euro-currencies. The negative autocorrelations remain clearly present in the first and last subperiods. Unsurprisingly, in the turbulent transition period they are less pronounced, statistically as well as algebraically. Note that for the ITL, with its wide band, the autocorrelations are weaker, but for core members the coefficients are large not just statistically but also economically, with averages in excess of -0.20 and individual cases up to -0.50. We conclude that there was a substantial predictability in daily as well as weekly exchange-rate changes.

2 Regression tests of UIP, weekly data

2.1 Standard tests

According to the UIP hypothesis, expected exchange rate changes should be offset by differentials in the interest earned, or, equivalently, by the forward premium. Formally, the hypothesis is $E_{t-1}(\tilde{s}_t) = FP_{t-1}$, where $\tilde{s}_t$ denotes $[S_t - S_{t-1}]/S_{t-1}$, the simple percentage change in the exchange rate, and FP_{t-1} denotes the forward premium set at time $t-1$ for delivery at t.[5] A familiar test is to run the Cumby-Obstfeld-Fama (COF) regression of exchange rate changes on forward premia, possibly augmented by other variables X_{t-1} known at $t-1$:

$$E_{t-1}(\tilde{s}_t) = \kappa_0 + \kappa_1 FP_{t-1} + \kappa_2 X_{t-1}. \tag{2.1}$$

The UIP hypotheses predicts $\kappa_0 = 0 = \kappa_2$ and $\kappa_1 = 1$.

In Table 2 we summarize our results for equation (2.1) on weekly data against the DEM. We use two equation-by-equation estimators, OLS and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) (1,1), and two system estimators, Full Information Maximum Likelihood (FIML) and Generalized Method of Moments (GMM). Estimates are provided for the entire data set and for each of the three subperiods defined before. Since the forward premium is almost a unit-root process, the regular t-tests vastly overstate the significance; thus, we merely list the estimates themselves. We add s_{t-1} as the obvious candidate for an additional regressor X_{t-1} in (2.1). The standard deviation for its coefficient, κ_2, is given in the header of each Panel in the Table.

In Panel A of Table 2 the overall picture is, at best, mixed. At 0.71, the average OLS slope for the forward premium is surprisingly good, in fact, and the GARCH figure is not much worse. Still, this simple mean of just five estimates, each of dubious and heterogenous precision, is not necessarily reliable. The median slopes are already substantially lower than the simple averages, and the system estimators tend to come up with the familiar negative slopes. Upon closer inspection, the positive equation-by-equation slopes are entirely due to the statistically suspect middle period, where the size of the estimates is, in addition, bizarre. In the larger subsamples (Panels A2 and A4), negative slopes dominate, and the recent figures are worse than the early ones. The evidence from the COF coefficients is, in short, not reassuring: DEM-based test results do not provide any better support for UIP, and there is no improvement over time.

While we observe no clear difference between intra-European versus other rates in Panel A, there is a sharp divide in Panel B, where ERM members still show massive negative first-order autocorrelation. Even though the forward premium has been added as a regressor, the κ_2s in

[5]The time subscripts reflect the moment the variable is known—so t for s, and $t-1$ for FP or for the risk-free rates for investments between times $t-1$ and t. We compute forward premia using one-week interest rates taking into account the two-working-days delivery rule in spot and forward markets, the 365-days-per-year convention for GBP and (pre-1999) BEF interbank money markets, and the 360-days-per-year convention for other currencies.

Table 2: Cumby-Obstfeld-Fama Tests of UIP

$$E_{t-1}(\tilde{s}_t) = \kappa_0 + \kappa_1 FP_{t-1} + \kappa_2 \tilde{s}_{t-1}$$

Panel A: COF slope coefficient (κ_1)												
	coefficients for individual currencies										central values	
	BEF	NLG	DKK	FRF	ITL	CHF	GBP	JPY	CAD	USD	avg	med
	A1. Total period (1985/6 - 1998/3)											
OLS	-0.05	0.38	0.69	-0.18	-0.33	1.17	2.07	2.75	0.26	0.30	0.71	0.34
GARCH	-0.27	-0.06	0.28	-0.30	0.03	0.97	2.25	2.75	0.60	-0.64	0.56	0.15
FIML	-0.29	-0.17	-0.21	-0.43	-0.03	0.08	0.02	0.02	-0.01	0.02	-0.10	-0.02
GMM	-0.96	0.12	-0.38	-0.57	1.13	0.22	1.76	3.68	-0.15	0.09	0.49	0.10
	A2. Early ERM(tight band, 1985/6 - 1992/8)											
OLS	-0.37	-0.21	1.71	-0.33	-0.44	0.38	0.80	-0.42	-1.90	-3.96	-0.47	-0.35
GARCH	-0.37	-0.36	0.71	-0.41	0.30	0.07	0.83	-1.80	-2.60	-4.69	-0.83	-0.37
FIML	-0.58	-0.28	1.49	-0.67	-0.28	0.17	-0.62	-0.96	-1.48	-4.42	-0.76	-0.60
GMM	-0.34	-0.39	0.70	-0.40	1.02	0.22	-0.67	-0.33	-1.85	-2.59	-0.46	-0.36
	A3. Sept 92 end 94 (turbulence, 1992/9-1993/12)											
OLS	1.74	0.89	-2.42	2.48	-12.53	9.31	3.44	63.30	9.06	57.92	13.32	2.96
GARCH	2.39	0.18	-2.37	1.61	-12.52	12.00	3.33	62.90	15.52	48.96	13.20	2.86
FIML	0.57	-0.04	-3.78	-0.62	-3.81	7.13	5.35	12.10	-5.43	19.29	3.08	0.27
GMM	-0.74	0.61	-13.29	18.43	-11.11	7.25	8.16	333.09	8.50	81.50	43.24	7.71
	A4. Late ERM(wide band, 1994/1 - 1998/3)											
OLS	-1.11	-4.31	-2.35	-1.55	-3.90	-5.52	-7.23	-7.20	-2.66	-19.06	-5.49	-4.10
GARCH	-0.58	-1.94	-1.90	-1.55	-3.89	-2.37	-7.23	-7.20	-2.68	-19.07	-4.84	-2.53
FIML	-2.18	-4.18	-2.22	-1.85	-2.71	-4.15	-1.74	0.31	-5.08	-23.64	-4.74	-2.47
GMM	1.32	-3.49	-18.33	-1.36	25.55	-22.89	-7.88	-8.53	-3.00	-28.11	-6.67	-5.69
Panel B: autoregression coefficient (κ_2)												
	coefficients for individual currencies										averages	
	BEF	NLG	DKK	FRF	ITL	CHF	GBP	JPY	CAD	USD	ERM	$\overline{\text{ERM}}$
	B1. Total period (1985/6 - 1998/4), $\sigma(\kappa_2) = 0.039$											
OLS	-0.28	-0.16	-0.18	-0.48	-0.04	0.10	0.01	0.02	-0.01	0.01	-0.23	-0.02
GARCH	-0.38	-0.24	-0.12	-0.44	-0.00	-0.00	-0.00	0.01	-0.01	0.04	-0.24	-0.05
FIML	-0.29	-0.17	-0.21	-0.43	-0.03	0.08	0.02	0.02	-0.01	0.02	-0.23	-0.02
	B2. Early ERM(tight band, 1985/6 - 1992/8), $\sigma(\kappa_2) = 0.052$											
OLS	-0.35	-0.30	-0.14	-0.51	-0.03	-0.03	0.00	-0.01	0.03	-0.05	-0.27	-0.06
GARCH	-0.38	-0.28	-0.07	-0.52	-0.02	-0.12	0.01	0.01	0.04	-0.02	-0.25	-0.06
FIML	-0.35	-0.29	-0.12	-0.46	-0.03	0.01	0.04	0.02	0.04	-0.02	-0.25	-0.03
	B3. Sept 92 end 93 (turbulence, 1992/9 - 1993/12), $\sigma(\kappa_2) = 0.12$											
OLS	0.01	-0.05	-0.22	-0.44	-0.03	-0.09	0.06	0.08	0.03	-0.12	-0.15	-0.01
GARCH	-0.15	0.00	-0.25	-0.35	0.03	-0.00	0.06	0.08	0.10	-0.21	-0.14	-0.02
FIML	-0.13	-0.09	-0.31	-0.39	0.05	-0.06	0.08	0.05	-0.04	-0.04	-0.17	-0.03
	B4. Late ERM(wide band, 1994/1 - 1998/3), $\sigma(\kappa_2) = 0.066$											
OLS	-0.39	-0.14	-0.18	-0.27	-0.09	0.09	-0.05	-0.02	-0.14	0.09	-0.21	-0.07
GARCH	-0.43	-0.22	-0.17	-0.27	-0.06	0.09	-0.06	-0.02	-0.14	0.11	-0.21	-0.07
FIML	-0.37	-0.16	-0.16	-0.25	-0.10	0.05	-0.02	0.01	-0.09	0.07	-0.23	-0.05

Key to Table 2. The regressands s_t are weekly percentage changes in the exchange rate against the DEM, the regressors are the beginning-of-period one-week forward premium (FP_t) and the lagged regressand. The estimation methods are OLS, Full Information Maximum Likelihood (FIML) , Generalized Method of Moments (GMM), and Generalized Autoregressive Conditional Heteroscedasticity (GARCH). The ρ's produced by SAS' GMM were absurd and are omitted. The central values shown are, in the top part, the mean and the median, and in the lower part, the mean for the ERM core currencies (BEF, NLG, DKK, FRF, CHF, the latter an informal member) and the other ones.

Table 3: : Tests of UIP on extreme v. modal FPs

$$E_{t-1}(\tilde{s}_t) = [\kappa_0 + \lambda_0 I(p)_{t-1}] + [\kappa_1 + \lambda_1 I(p)_{t-1}]FP_{t-1}.$$

coeff	regression coefficients for individual currencies										central values	
	BEF	NLG	DKK	FRF	ITL	CHF	GBP	JPY	CAD	USD	avg	med
	split at the 60th percentile											
κ_1	0.73	-1.61	0.81	-0.17	-2.62	0.93	0.78	-2.45	6.91	-1.15	0.22	0.28
λ_1	0.96	1.06	-0.06	1.34	5.21	2.09	-0.61	2.12	-8.06	1.68	0.57	1.20
	split at the 80th percentile											
κ_1	0.64	-0.68	0.94	0.55	-0.51	-0.43	0.42	-2.06	2.24	1.27	0.24	0.48
λ_1	-1.13	-1.40	-0.55	1.06	3.28	-0.54	-0.49	2.49	-2.81	-3.81	-0.39	-0.54
	split at the 90th percentile											
κ_1	-0.58	0.31	0.17	0.01	-1.48	0.54	2.16	-0.14	0.53	0.14	0.17	0.16
λ_1	-0.02	2.27	1.27	0.63	3.21	-0.61	1.32	2.58	0.94	69.73	8.13	1.29
	split at the 95th percentile											
κ_1	-0.34	-0.38	0.52	0.32	0.53	-0.55	0.28	-0.50	1.50	-1.02	0.04	-0.03
λ_1	-2.22	-1.02	1.01	2.33	6.50	2.81	-1.16	-0.82	-2.45	-124.19	-11.92	-0.92

Key to Table 3. The regressands (s_t) are weekly percentage changes in the exchange rate (against the DEM), the regressors are the beginning-of-period one-week forward premiums (FP_t). The intercept and slope coefficient are allowed to differ depending on whether the observation belongs to the p percent highest in terms of cross-sectional variation (Mahalonobis Distance), where p = 5, 10, 20, 40 percent. Estimation is by SUR.

Table 2 are strikingly similar to the ρ_1s in Table 1. Thus, forward premia do not at all pick up the predictability inherent in the negative autocorrelation of s. The significance of the lagged changes is puzzling: the phenomenon is quite obvious, there are no near-unit-root complications with the lagged change as the regressor, and if this is to be a missing-variable phenomenon, we'd need a risk premium that, miraculously, perfectly mirrors the lagged changes.

2.2 Tests on "extreme" observations

One potential explanation of the poor results is that, because of transaction costs or risk premia, the forward premia are noisy estimators of the true conditional expectation, creating the standard errors-in-the-regressor bias towards zero. To attenuate this, Nissen (1997) and Huismans *et al.* (1998) look at subsamples where forward premia are large, hoping that for these observations the expected changes are unusually large, too. If so, the better signal-to-noise ratio should increase the COF regression coefficients back towards unity.

We adopt the original Bilson (1984) formulation, a variant of (2.1):

$$E_{t-1}(\tilde{s}_t) = [\kappa_0 + \lambda_0 I(p)_{t-1}] + [\kappa_1 + \lambda_1 I(p)_{t-1}]FP_{t-1}. \tag{2.2}$$

In (2.2), the indicator $I(p)_{t-1}$ equals unity if, on day $t-1$, the forward premium is "large", that is, belongs to the top p percent of the ranked observations, with p being set equal to 40, 20, 10, or 5 percent; otherwise, $I(p)_{t-1}$ equals zero. [6] The regressions use GARCH(1,1).

Table 3 provides the crucial results, and they are not in favor of UIP. As we go down the table, we do not see the average κ_1s trend upwards. Nor do we see a λ_1 that is systematically positive and trending upwards as we go down the table. Thus, the simple errors-in-variables-like effect Nissen or Huisman *et al.* had found in their monthly date against the USD is not present in our numbers.

3 A trading rule test

If intra-ERM rates are to a non-trivial extent predictable and one-week interest rates do not pick this up, average returns from trading must be positive, at least before costs. To discover whether the potential gains are large, before and after costs, we formally test a trading rule. Ideally, we would like to take transaction costs into account at every trade. While Datastream has bid-ask rates, these are indicative quotes whose spread substantially overstates the spreads in any individual market maker's binding quotes and *a fortiori* overstate the difference between the market's best bid and ask. To still obtain an approximate answer to the question whether the returns exceed the two-way costs, we keep track of the number of trades and compute the average before-cost profit per trade, as described in the next section. This average profit per trade can then be judged against the limited information we have about transaction costs—which is an order of magnitude rather than precise best bids and asks.

3.1 The Trading Rule

The purpose of this section is not to find the optimal trading rule, unlike many of the papers cited in the introductory section. Rather, we want to show that even the simple linear relation picked up in our UIP tests provides information with clear economic significance. The fact that more sophisticated rules would have done even better just reinforces that point.

Our test assumes daily trading. As we have mentioned, at the daily horizon European rates against the DEM tend to exhibit negative first- and second-order autocorrelation. The linear trading rule that tries to measure the potential gains from this phenomenon is implemented

[6]Huisman *et al.* work with panel data and a restriction of equal betas across currencies. Their high/low criterion is, accordingly, based on the ranked dispersions of the forward premia within each cross-section. We do not follow their approach as, in our sample, the cross-currency constraint is rejected.

in calendar time[7] and works as follows. We take the DEM as the home currency. Using two years of past data, we estimate the first- and second-order correlation coefficients. Periodically these estimates are updated using the most recent 2-year sample. At any date $t-1$, then, our contrarian forecast for the next-day change will be a partial reversal of the recent changes:

$$(\widehat{s_t - FP_{t-1}}) = \rho_{-1}\,(s_{t-1} - FP_{t-2}) + \rho_{-2}\,(s_{t-2} - FP_{t-3})\,. \tag{3.3}$$

Whenever the predicted net return against the DEM is positive and larger than a pre-set filter ϕ, we receive a "buy FX" signal; likewise we get a "sell FX" message whenever the predicted movement is more negative than $-\phi$.

We consider three (related) trading rules, the first of which is a "pooled" trading rule, that is, one where both buying and selling are possible. Under this rule, upon a "buy" signal we go long FX and short DEM; after the "sell" recommendation we switch to long DEM and short FX; and when there is neither a buy nor a sell signal we do nothing.[8] Formally, in the pooled trading rule we set $D_{b,t-1} = 1$ whenever there is a buy recommendation and 0 otherwise, and we likewise set $D_{s,t-1} = -1$ whenever there is a sell recommendation and 0 otherwise. In the equations below, the first two show the raw daily returns on the asset and liability accounts, respectively (subscripts A and L), where the Ds activate either a FX or a DEM position. The last equation defines the net return (NR) as the return from the asset account minus the return from the liability account:

$$\begin{aligned}
R_{A,t} &= D_{b,t-1}(s_t + r^*_{t-1} + s_t r^*_{t-1}) + (1 - D_{b,t-1})r_{t-1}, \text{ where } D_b = \{0,\,1\} && (3.4)\\
R_{L,t} &= (1 + D_{s,t-1})r_{t-1} - D_{s,t-1}(s_t + r^*_{t-1} + s_t r^*_{t-1}), \text{ where } D_s = \{0,\,\text{-}1\} && (3.5)\\
NR_t &= R_{A,t} - R_{L,t}\\
&= (D_{b,t-1} + D_{s,t-1})[(s_t + r^*_{t-1} + s_t r^*_{t-1}) - r_{t-1}], && (3.6)
\end{aligned}$$

where r_{t-1} (r^*_{t-1}) is the one-day return on a DEM (FX) money-market investment and between dates $t-1$ and t and s_t the percentage exchange-rate change over the same period. We recognise $[(s_t + r^*_{t-1} + s_t r^*_{t-1}) - r_{t-1}]$ as the return, measured in DEM, on a one-day FX investment, in excess of the DEM return; multiplying by $(D_{b,t-1} + D_{s,t-1})$, this excess return is "weighted" by $+1$ in case of a buy signal, -1 in case of a sell, and a zero in case of no signal.

[7] See Bjerring et al. (1983) for the difference between event-time and calendar-time studies.

[8] It can be verified that, in the equations below, "doing nothing" is shown as having DEM both as the asset and the liability, so that the net return is zero. We need this seemingly Byzantine twist for the annualization, *infra*, where both the asset and liability sides need to be fully invested all the time.

We also want to test whether the gains are symmetric. For this purpose we test a separate "buy" strategy, one where $D_{s,t-1}$ always remains zero (that is, upon bad news we liquidate a long FX position but we never actually shortsell FX); and we likewise implement a "sell" strategy where $D_{b,t-1}$ is never switched to unity: upon a buy signal we stop shortselling FX (if we were short at all) but we never actually go long FX. These one-directional results are relevant to a liquidity trader, who is typically interested in a transaction of a particular type. But these results can also provide insights related to the forward puzzle, and more specifically whether Peso risk is likely to be a major factor or not.[9] Given the reputation of the home currency, the DEM, for ERM members only one type of parity change is conceivable: a devaluation of FX. Peso risk, if any, should show up especially after a "buy FX" signal (which follows a drop of FX), and less after a "sell FX" signal because then the FX has picked up, recently. In short, a positive difference between the average "buy" and "sell" returns would be consistent with differential Peso risk for ERM members.

3.2 Economic and statistical significance measures

For the purpose of interpreting the average daily returns obtained this way for various filters and currencies, it is useful to correct for two obvious sources of differences in risk across currencies. First, the average risk premium may differ between, say, ITL and NLG. Second, there can be substantial differences as to the times spent long and short each currency. We can correct for these by considering a constant control strategy which is, on average, as risky as the trading rule. Specifically, for each currency we compute the averages of D_b and D_s, and define a static control strategy where we hold a constant position, equal to $\overline{D}_b + \overline{D}_s$, instead of the time-varying one in (3.6). The excess net return (*XNR*) then is defined as the net return in excess of the net return on the control strategy:

$$XNR_t = [(D_{b,t-1} + D_{s,t-1}) - (\overline{D}_b + \overline{D}_s)][(s_t + r^*_{t-1} + s_t r^*_{t-1}) - r_{t-1}]. \tag{3.7}$$

To assess the statistical significance we consider the expected value:

$$\mathrm{E}(XNR) = \mathrm{cov}[(D_b + D_s), (s + r^* + sr^* - r)]. \tag{3.8}$$

This means that the significance of the mean excess return can be tested in the same way as the significance of a covariance or a simple regression coefficient. Specifically, one regresses the

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[9] A peso risk is a small probability of a huge event. The event is so huge that it affects the true expectation, but the probability is so small that the researcher does not observe the event and, therefore, mis-estimates the expectation.

net return $(s + r^* + sr^* - r)$ on the trading signal $(D_b + D_s)$. This test can be done separately for the pooled, buy, and sell rules. We use OLS with Newey-West's corrected t-statistics.

The above tests bear on mean excess returns per day. To judge the economic significance we complement this in two ways. First, to see whether returns are sufficient to recover transaction costs, we compute average returns per run of signals of the same sign. Second, to assess the likelihood of competing explanations of the forward puzzle, we cumulate the returns over long periods and compute *p.a.* returns. The details are as follows.

In the first variant we compute the average return per run of consecutive signals D of the same sign. Thus, in computing this average, we assume that the trader does not automatically close out at the end of each day, but waits until the signal either becomes zero or changes sign. Within a given run of similar signals, the returns on the assets and liabilities are cumulated separately[10] and the net value is computed at the end of the run. To the speculator, this average return per run is more relevant than the average return per buy or sell day since the speculator probably can hold positions longer than one day and incurs the costs only once.

In the second variant we cumulate the returns over long periods and compute *p.a.* returns. Again, asset returns are cumulated separately from liability returns, and we compute the final net value as

$$\text{net final value} = \prod_{t=t_1}^{t_n} (1 + R_{A,t}) - \prod_{t=t_1}^{t_n} (1 + R_{L,t}). \tag{3.9}$$

For each strategy, the *p.a.* average net return is obtained by computing average returns for each of the legs separately:

$$\text{average } p.a. \text{ net return} = \sqrt[N]{\prod_{t=t_1}^{t_n} (1 + R_{A,t})} - \sqrt[N]{\prod_{t=t_1}^{t_n} (1 + R_{L,t})}, \tag{3.10}$$

where N is the time between starting date t_1 and end date t_n measured in years rather than trading days. The *p.a.* excess return then is computed as the above net return minus the analogous net return on the constant-portfolio control strategy.

[10] Directly compounding the net returns, or *a fortiori* excess returns, would be hard to interpret since there is no implementable strategy that provides this cumulative payoff.

3.3 Risk-free investments

As mentioned, in Datastream the one-day spot rates are unavailable for most of the period. We use returns from holding a 7-day CD for one day,

$$r_t = \frac{1 + i_{t,t+7} * (7/36\text{X})}{1 + i_{t+1,t+6} * (6/36\text{X})} - 1, \tag{3.11}$$

where $i_{t,t+7}$ is a *p.a.* simple interest rate for a 7-day deposit; and 36X equals 365 for BEF and GBP, and 360 for other currencies. The numerator shows the face value of a 7-day investment made at t, and the denominator is the 6-day discount factor the next day. To implement this, we need to assume that $i_{t+1,t+6} = i_{t+1,t+7}$, which, traders confirm, is acceptable. The results are not at all sensitive to this approximation. In an exploratory run, for instance, we simply took Datastream's "representative short-term" interest data to be one-day spot rates (even though, in reality, they may be three-month rates) and found essentially the same results. Indeed, the picture hardly changes even if we set all rates equal to zero. (These results are available on request.) The reason for the near-irrelevance of interest rates is their independence of exchange-rate changes plus the fact that, via the control strategy, any maturity-related bias largely disappears.

3.4 Empirical Results

Table 4, Panel A shows total-period *p.a.* net excess returns and t-tests on the average daily net excess return, for various values of the filter. We also provide means for ERM and non-ERM currencies. There is a classification problem with the CHF (not a member, but widely viewed as *de facto* pegged) and the ITL (a member, but with a much wider band). Somewhat arbitrarily, we put the CHF into the ERM group and the ITL not; this is conservative in the sense that it blurs the differences between the subsamples.

We note that across all filters the returns are unanimously positive for the continental currencies, while they are unsystematic and algebraically small for the other currencies. The returns are systematically significant for core ERM currencies, most of the time also for the CHF and ITL, but never significant for the GBP and the control group in the strictest sense (CAD, JPY, USD). It clearly pays to decrease the filter from 10 bp to 5 or even 1 bp, but further refinements no longer add anything substantial. The trading rule produces rather impressive excess returns: the ERM-group average for the 1bp rule is 14 percent, and individual-currency results range between 8 and 19 percent (between 300 and 650 percent cumulative over eleven

Table 4: Excess *p.a.* returns for all filters

	coefficients for individual currencies										averages	
	BEF	NLG	DKK	FRF	CHF	ITL	GBP	JPY	CAD	USD	ERM	$\overline{\text{ERM}}$
ϕ (bp)	Panel A: Pooled (buy and sell), total period (1985/6 - 1987/3)											
10 bp	9.44	10.4	8.42	9.94	2.19	1.3	-0.18	3.49	0.76	-0.92	8.08	0.89
t-test	*12.61	*11.03	*10.23	*16.81	*3.33	0.97	-0.16	1.12	0.64	-1.17		
5 bp	15.1	13.35	10.12	13.29	3.51	4.41	0.9	4.13	0.1	1.47	11.07	2.20
t-test	*16.54	*12.55	*10.08	*17.45	*3.93	*2.64	0.50	0.98	0.08	1.04		
1 bp	19.35	15.11	11.9	15.62	8.72	6.46	0.28	2.14	1.17	3.83	14.14	2.78
t-test	*16.71	*12.19	*9.35	*16.05	*6.78	*3.20	0.09	0.43	0.42	1.60		
.5 bp	19.20	15.61	12.44	15.78	8.48	5.74	-1.05	3.63	1.34	4.11	14.30	2.75
t-test	*16.54	*12.55	*10.08	*17.45	*3.93	*2.64	0.50	0.98	0.08	1.04		
.1 bp	19.26	15.28	12.49	15.75	9.48	5.14	-2.9	5.11	1.73	4.12	14.45	2.64
t-test	*15.82	*11.38	*9.21	*15.23	*6.50	*2.38	-0.90	0.92	0.56	1.46		
smpl	Panel B: Pooled (buy and sell), three subperiods, ϕ=10bp											
1985-	8.84	11.42	4.09	6.63	0.56	0.02	-0.15	5.19	0.72	-0.10	6.31	1.14
t-test	*5.15	*7.92	*5.85	*11.60	0.69	0.17	-0.12	1.30	0.50	-0.29		
1992-	15.65	28.09	18.20	23.52	1.36	9.83	6.61	18.04	5.84	3.85	17.36	8.83
t-test	*8.58	*8.62	*8.25	*10.86	*4.42	*6.06	1.09	1.25	1.06	1.24		
1994-	8.31	5.71	8.49	8.54	3.27	0.01	-1.80	-1.05	-0.41	-2.49	6.86	-1.15
t-test	*10.01	*4.69	* 6.50	*10.05	*3.16	0.04	-1.41	-0.26	-0.27	-2.28		
rule	Panel C: Total period, buy versus sell, various filters											
10buy	4.68	6.07	4.52	5.00	1.28	0.68	-0.56	2.23	-0.62	-0.77	4.31	0.19
t-test	*7.85	*8.14	*7.65	*13.32	*4.24	0.65	-0.66	1.24	-0.71	-1.60		
10sell	4.76	4.32	3.89	4.94	0.91	0.61	0.39	1.26	1.38	-0.15	3.76	0.70
t-test	*11.12	*10.94	*8.51	*13.83	1.72	1.14	0.39	0.40	1.64	-0.47		
t_{b-s}	-0.11	2.07	0.84	0.12	0.61	0.06	-0.72	0.27	-1.65	-1.07		
5buy	8.13	7.74	5.41	6.85	2.08	2.83	-0.17	3.44	-1.35	0.95	6.04	1.14
t-test	*12.61	*10.00	*8.26	*14.62	*4.03	2.25	-0.08	1.51	-0.93	1.17		
5sell	6.97	5.61	4.71	6.44	1.43	1.58	1.07	0.69	1.44	0.52	5.03	1.06
t-test	*13.58	*11.64	*9.02	*15.36	*2.39	2.23	0.85	0.10	1.09	0.45		
t_{b-s}	1.29	0.91	0.98	1.36	0.73	1.08	-0.04	-0.01	0.19	0.28		
1buy	10.23	7.99	6.43	8.30	4.73	4.09	-0.15	-0.59	0.86	2.19	7.54	1.28
t-test	*16.04	*10.79	*8.73	*15.47	*6.77	*3.24	0.01	0.00	0.64	1.69		
1sell	9.12	7.12	5.48	7.31	3.99	2.37	0.44	2.74	0.31	1.64	6.60	1.50
t-test	*15.86	*11.74	*8.78	*14.81	*5.50	*2.45	0.16	0.82	0.12	1.10		
t_{b-s}	1.41	*2.34	0.84	0.65	0.82	0.87	-0.50	0.38	-1.42	0.30		

Key to Table 4. We use daily data, June 14, 1985 to April 1, 1998 with the DEM as reference currency. There is a buy signal ($D = 1$) whenever the exchange-rate change, as predicted by the AR(2) equation, exceeds the filter size ϕ; and there is a sell signal ($D = -1$) when the predicted return is below $-\phi$. On $D = 1$ (-1) we go long FX (DEM) and short DEM (FX), while on $D = 0$ both the short and long side are DEM. Returns are on holding a 7-day DEM or FX riskfree investment for one day. In the control strategy, we follow a static rule of always investing $\bar{D}$ units (where $\bar{D}$ is the average position for that currency over the entire sample period). The t-tests are on the mean net return (asset minus liability) per day in excess of the net return from the trading strategy, and an asterisk indicates significance at 1% one-sided. The returns themselves are compounded and annualized. The two average returns in the rightmost columns are computed over the first and second sets of five currencies, respectively. Subperiods are (*i*) is until September 1, 1992; (*ii*) September 92 till end 93; (*iii*) as of 1994. In the third part of the table, signals $D = -1$ are set to $D = 0$ in the buy-only rule, and signals $D = 1$ are set to $D = 0$ in the sell-only rule. The rule "10buy" refers to a buy-only game with filter 10, and so on. The t-test on the difference between the buy and sell returns is indicated as t_{b-s}.

years[11], that is). But even the widest filter, 10bp, still pays out a respectable excess average return of 8 percent.

To verify the intertemporal stability and internal validity of the results, and to further reduce potential problems of heteroskedasticity, we run all tests also on subperiods, using again the tranquillity-versus-turbulence criterion. To preserve space we just show these subperiod results for the worst-performing filter, 10bp. The summary is in Panel B of Table 4. Despite the much smaller sample sizes, only one cell loses its significance rating (CHF in the first period). The numbers remain in remarkable agreement with the total-sample results: almost unanimously clear and positive returns per subperiod for the core-ERM currencies, less impressive but positive returns for the CHF and ITL, and essentially random results for the GBP and the control currencies JPY, CAD, and USD. For the other filters the results are generally stronger but otherwise show the same patterns across currencies and periods.

In Panel C of the table we check whether the profits stem mostly from the long positions, or the short ones. Results for the 0.5- and 0.1-bp filters, being too similar to the 1-bp results, are omitted. It turns out that the returns from the buy-only and sell-only rules are quite comparable. Each is significant in its own for the hard-core ERM members, often so for ITL and CHF, and never so for the outside currencies. Judging by t-tests, the difference between buy and sell is never significant at the 1-percent level except in one case (out of 18—*i.e.* three trading rules $\times$ six continental currencies). True, another case is almost significant (with $t =$ 2.07), but both the significant and the almost-significant ts occur for the same currency, the NLG; and if we want to cite this as evidence of Peso-type risks, then the NLG is surely the least convincing candidate.

From these buy- or sell-only results we conclude that, for liquidity traders whose transaction costs are irrelevant, there would have been substantial gains from using the trading rule. Of course, being cumulative returns before transaction costs, the net excess payoffs reported in Table 4.C are representative only for liquidity traders that have to do a transaction every day (and of a similar size every day). To provide an idea of the profitability in a more general situation, Table 5 reports the mean profit per run and per signal for various filters, and for the best- and worst-performing filters also the subperiod results. We see that the large filters, which produced the lowest *p.a.* net excess returns, actually provide the highest profits per signal; thus, in terms of cumulative returns the problem with the large filters obviously is that

[11]We have thirteen years of data but lose two in estimating the ARIMA model.

Table 5: : Average Abnormal Returns per run and per signal, subperiod results for the largest and smallest filters

Sample	BEF	DKK	FRF	NLG	CHF	ITL	GBP	USD	JPY	CAD	
Panel A: average profit per run, %											
Filter	Strategy	BEF	DKK	FRF	NLG	CHF	ITL	GBP	USD	JPY	CAD
0.100	buy	0.20	0.24	0.23	0.24	0.19	0.08	0.06	0.04	0.13	0.08
	sell	0.23	0.21	0.22	0.22	0.10	0.07	0.01	0.07	0.04	0.12
0.050	buy	0.17	0.19	0.15	0.17	0.12	0.09	0.03	0.04	0.07	0.07
	sell	0.18	0.18	0.16	0.16	0.08	0.10	0.03	0.01	0.05	0.03
0.010	buy	0.14	0.15	0.11	0.12	0.08	0.08	0.02	0.01	0.04	0.02
	sell	0.14	0.14	0.11	0.12	0.06	0.05	0.02	0.02	0.04	0.01
0.005	buy	0.13	0.14	0.10	0.12	0.07	0.09	0.02	0.02	0.03	0.01
	sell	0.14	0.14	0.10	0.12	0.05	0.05	0.02	0.00	0.03	0.01
Panel B: average profit per signal, %											
0.100	buy	0.16	0.19	0.17	0.19	0.17	0.07	0.05	0.03	0.12	0.07
	sell	0.18	0.17	0.17	0.18	0.08	0.06	0.01	0.07	0.04	0.11
0.050	buy	0.12	0.13	0.10	0.12	0.09	0.06	0.02	0.04	0.06	0.06
	sell	0.14	0.13	0.12	0.12	0.06	0.09	0.03	0.01	0.05	0.03
0.010	buy	0.08	0.08	0.06	0.07	0.04	0.05	0.02	0.01	0.03	0.01
	sell	0.09	0.08	0.06	0.07	0.03	0.03	0.01	0.02	0.02	0.00
0.005	buy	0.07	0.07	0.06	0.07	0.04	0.05	0.01	0.02	0.02	0.00
	sell	0.08	0.07	0.06	0.07	0.03	0.03	0.01	0.00	0.02	0.01

Key to Table 5. There is a buy signal (D=1) whenever the absolute value of the exchange-rate change, as predicted by AR(2), exceeds the filter; and there is a sell signal (D=1) when the predicted return is below minus the filter. The trade, if any, is a one-working-day forward sale or purchase depending on the sign of the predicted change. The table shows average excess returns (AARs) per trade and per run, for strategies where both selling and buying is allowed ("pooled"), as well as for strategies with either just buying or just selling. The AARs are averages of gross returns over the entire period (June 14, 1985 to April 1, 1998), in excess of the return from a static trading strategy consisting of always buying forward $\bar{D}$ units (where $\bar{D}$ is the average position over the entire sample). For the AAR per signal we assume that the trader liquidates every day. For the AAR per run we assume that when a signal D is followed by another one of the same signs, then the trader rolls over her position until the run of identical Ds is finished.

there are not enough of these trading opportunities. The question to be settled is whether these average returns per trade exceed the transaction costs. This is one of the topics of the concluding section.

4 Discussion and Conclusion

We discuss the three potential explanations advanced by Froot and Thaler (1990)—a regular risk premium, Peso risk, and learning—and the transaction cost view by e.g. Baldwin (1990).

- *Learning.* Unlike in the case of the US, there was no pronounced shift in monetary policy in the ERM. Also, the system was well known by the time our data start.

- *A regular risk premium?* The regular risk premium is a covariance with a stochastic discount factor which, in turn, is usually specified as the return on a portfolio or a combination of portfolios. We focus on the risk premium as specified by the standard CAPM or its international version (InCAPM). In these models the portfolios are, in case of the CAPM, the market portfolio and, for the InCAPM, a combination of the world market and the various countries' T-bills. In the CAPM, the spot rate's beta can never be large because the R^2 of an exchange-rate market-model regression is invariably tiny:[12]

$$\beta_i = \sqrt{\frac{\mathrm{var}(s_i) - \mathrm{var}(e_i)}{\mathrm{var}(r_m)}} \ll 1,$$

  where r_m is the market return and $\mathrm{var}(e_i)$ the residual variance in the regression of s_i on r_m, which is almost as large as $\mathrm{var}(s_i)$ itself. Thus, with such a small beta, even if the risk premium on the market would be 10 percent we would never get anywhere near a 10-percent average for an exchange rate. True, this argument assumes that the market sensitivity is constant, which is not necessarily true. But bear in mind that our calculations removed the average risk premium from the returns, and that half of the excess return comes from being short; so if we are to explain our 15 percent excess return (and half of it from shorting), via a wildy fluctuating beta, then half of the time the beta needs to be of the order of magnitude of +1, and half of the time of the order of -1. This is, again, inconceivable.

  If the CAPM cannot explain an excess return of 15 percent, might the InCAPM do so? In

[12] See for instance, Allayannis (1996) for a review.

the international version an own-variance risk premium is added (Sercu, 1980):

$$E(s_i + r_i^* - r) = A_w \cdot \mathrm{cov}(s_i, r_w) + (1 - A_i)\frac{W_i}{W_w}\mathrm{var}(s_i),$$

where r_w is the world-market return; A_i (A_w) is relative risk aversion for the country-i (world) investor; and W_i (W_w) is country i's (the world's) invested wealth. But again it is implausible that returns of 10 or 20 percent *p.a.* would be explained by the new risk premium: the consensus is that relative risk aversion exceeds unity, making the additional risk premium negative.

- *Peso Risk?* Peso problems are *a priori* not likely to explain the near-zero slopes for intra-European rates. For one thing, while there must have been more-than-occasional episodes of re-alignment fears in the sample period, such re-alignments have actually occurred fairly frequently. Also, they were small, *ex post*: Sercu and Uppal (1995, pp 364-65) report an average devaluation jump size of 4 percent. Nor can one argue that individual *ex ante* jumps might have been much bigger: the understanding in the ERM was that a devaluation should just undo the cumulative change in the real rate since the previous realignment. Thus, the idea that 14 percent is the product of a small probability times a huge jump-size is utterly implausible.

  A second line of argument against the Peso explanation is that our COF regression coefficients for non-European rates are at least is bad as the ERM ones. If this is to be explained by Peso risk, the floating-rate data would have to be more exposed to that risk—but it is hard to conceive what type of catastrophic event could occur in the case of floating rates. Third, if Peso risk is present, it should have shown up in our trading-rule results: going long FX after it has dropped should be the position with comparatively more peso risk, not going long DEM after a rise of FX. That is, the returns from buy-only should exceed those from sell-only. While this algebraically true, the observed differences are pairwise insignificant, and never amount to more than a fraction of the 14 percent we have to explain away.

- *The gains are small and risky.* For a committed exporter or importer who is trading very frequently, judicious exercising of the option to postpone a purchase or a sale would increase revenue by several percentage points. Detailed subperiod results (available on request) show that the trading rules never produced negative payoffs over any two-year interval.

- *Transaction costs wipe out any gains?* An exchange rate is quoted in at least four digits (think of a below-par EUR/USD) and often in five digits (like the USD/DEM, of old). In the mid 90s, binding quotes for USD/DEM were about three pips apart, and the market spread between best bid and best ask was occasionally as low as two or one pip (Lyons, 1998). Assuming, conservatively, a market spread of three pips and a DEM-per-USD rate of 15,000 pips, the two-way cost was *at most* 2bp. Of course, our data include lower-volume currencies, too, but 6bp is about the maximum for the rates we look at. From Table 5 it is unclear whether the small filters would have been profitable to round-trip speculators, but the larger filters, that pay off at least 10 percent per trade, have been profitable even after transaction costs. Thus, one cannot claim that transaction costs would have wiped out the gains we have observed.

Is the only remaining explanation, then, a market inefficiency, especially in light of the fact that gains exceed the transaction costs? Baldwin (1990) argues that it is not. Specifically, he points out, the observed return differentials should clearly exceed the costs before the arbitrageurs would rationally move in. True, the holder of DEM has the option to shift her funds into FX as soon as the expected total return on FX exceeds the return on DEM. However, she will normally wait until that option is sufficiently far in the money. The first reason is one that holds for ordinary options, too: the holder of an American-style option will not exercise as soon as it is in the money by a minute amount, but will wait until the payoff is big enough: immediate excercise would kill the (roughly) 50 percent probability that the exercise value increases over the next time interval, and the gains from moving deeper into the money outweigh the losses from moving back towards the money. The second reason for delayed exercise is that, if and when the investor has shifted her funds into FX, still sooner or later the return on DEM is bound to become more attractive again. But due to the transaction cost, she will then have to live with below-normal returns on FX until the loss is sufficiently big to warrant switching back to DEM. In short, to trigger trades, the return differential has to compensate for the transaction cost of moving into and out of FX, plus the possible regret from moving in too soon, plus the likely cost of reaping below-normal returns before moving out again. In light of this, the jury is still out on whether or not transaction costs justify inaction to the extent we have witnessed in our data.

We conclude by a brief wrap-up. One issue that hampers tests of UIP is that the market's expectations are unobservable. In this paper we are able to identify clear non-zero expectations from the exchange rate data themselves, for the simple reason that the ERM (or perceived dirty floating) induces statistically significant mean-reversion in daily and weekly exchange rates against the DEM. UIP hypothesizes that this predictability should be picked up by the one-week forward premium, but when running the Cumby-Obstfeld (1984), Fama (1984) regression tests of the unbiased expectations hypothesis at the one-week horizon, we obtain essentially zero coefficients for intra-EMS exchange rates (and the familiar negative coefficients for extra-EMS rates). These slopes are also quite unstable across estimation methods and periods. Lastly, lagged exchange rate changes remain significant when added to the regression, that is, forward premia seem to essentially ignore this source of predictability in exchange rates. Especially this last finding seems damaging to UIP: the mean-reversion is quite simple to detect, the lagged change is not at all a near-stationary regressor, and the idea that, over time, the risk premium would perfectly mirror the lagged changes looks far-fetched. Nor can one maintain that the phenomenon is economically trivial. We indeed test a trading rule, and find that for a sufficiently large filter the average profit per trade is larger than transaction costs. The size of the profits and the patterns from buy versus sell decisions allow us to reject the regular risk premium and the Peso hypotheses too, at least as being sufficient in themselves to explain the results. To figure out whether all this implies a market inefficiency, however, we need more insight into the effect of transaction costs on optimal trading.

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